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Time-Specific Disturbances in a Panel Stationarity Test

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Abstract

In this paper, we investigate the performance of a panel data stationarity test when cross-sectional correlation is modelled by a time-specific factor. Size distortions, that occurs especially when the number of cross sections is small, are documented. To eliminate these distortions, a new set of critical values is supplied. When investigating the rejection frequency under the alternative hypothesis, it is found that the panel data stationarity test that uses the supplied critical values maintain good power characteristics even when only a subset of the cross-sectional units have a unit root.

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1 Introduction

When testing for stationarity, unit roots and cointegration in the time-series setting, the power of the tests is to a large extent influenced by the number of observations available for the considered time series. When the time-series sample is short, the tests can have very low power, often failing to reject the null hypothesis even when it is false. However, by using time-series data for several cross sections, i.e. by applying panel data when testing for unit roots, stationarity and cointegration, more powerful inference is enabled. This was recognized e.g. by Quah (1994); Levin and Lin (1992, 1993); Levin et al. (2002); Im et al. (1997, 2003), who suggest various panel data unit root tests; by Hadri (2000), Hadri and Larsson (2005), Harris et al. (2005) and Shin and Snell (2006), who suggest panel data stationarity tests; and by Pedroni (1999), Pedroni (2004), McCoskey and Kao (1998), Westerlund (2005), Larsson et al. (2001) and Groen and Kleibergen (2003), who suggest panel data cointegration tests.[1][2]

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[1]Recent surveys of this rapidly developing research field can be found in Breitung and Pesaran (2008) and Choi (2006).

[2]Examples of empirical applications where panel unit root tests have been utilized are Lee and Wu (2004), Carrion-I-Silvestre et al. (2004) and Holmes (2002).

In the early panel data unit root, stationarity and cointegration literature, the assumption of cross-sectional independence was common. However, a growing body of research has documented the problems that can arise when dependency exits between the different cross-sectional units in the sample (see e.g. O'Connell, 1998; Jönsson, 2004). As a consequence, several different methods, that address the issue of cross-sectional dependency in the panel data unit root and stationarity framework, have been developed (see e.g. Bai and Ng, 2004a,b; Chang, 2002, 2004; Jönsson, 2005, 2006b; Moon and Perron, 2004; Pesaran, 2007; Phillips and Sul, 2003). The methods that are used to deal with cross-sectional dependency (CSD) involve orthogonalization of the series under consideration, extraction of common factors, augmentation of test regressions and bootstrap procedures that take cross-sectional dependency into account.

Within the panel data stationarity framework, Hadri (2000) suggest that the stationarity test of Kwiatkowski et al. (1992) can be applied to the cross-sectional units of a panel and that a panel data stationarity test can be constructed as the standardized mean over the cross-section specific test statistics. The test of Hadri (2000) differ from e.g. the panel unit root test of Im et al. (2003) in that the former takes stationarity as the null hypothesis while the latter takes a unit root as the null. Moments for the asymptotic Kwiatkowski et al. (1992) statistic are supplied by e.g. Hadri (2000) and, by utilizing the sequential limit arguments $T \to \infty$ followed by $N \to \infty$, the author shows that the panel data test statistic has a standard normal limiting distribution.[3,4] In order to account for a finite time-series dimension, Hadri and Larsson (2005) provide finite-T moments for the KPSS statistic under the assumption that the time series under consideration are serially independent, while approximate moments for the KPSS statistic with serially dependent time series are supplied by Jönsson (2006a). The moments of Hadri and Larsson (2005) can be used to obtain a panel data test statistic that is standard normally distributed as $N \to \infty$ for fixed T, while the moments of Jönsson (2006a) can be used to obtain an approximate standard normal distribution for the test statistic when T and N are fixed. By utilizing results from Monte Carlo simulations, Hadri and Larsson (2005) and Jönsson (2006a) show that inference can be improved by using the fixed-T moments, instead of the asymptotic moments, of the KPSS statistic.

When cross-sectional correlation, in the form of a time-specific disturbance, is allowed for in the panel data unit root and stationarity framework, Im et al. (1997) and Shin and Snell (2006) suggest that demeaning over cross sections should be employed in order to eliminate the dependence between cross sections. Even though some results indicate that demeaning over cross sections affects the small-N distribution of the panel data test under consideration (see e.g. Jönsson, 2006a,b), there is little knowledge about the small-N behavior of the Hadri and Larsson (2005) test when time-specific disturbances are present and accounted for.

In this paper, we study the performance of the panel data stationarity test of Hadri and Larsson (2005) when cross-section dependence is modelled by a time-

[3] From here on, the Kwiatkowski et al. (1992) test will be referred to as the KPSS test.

[4] T is used to indicate the number of time-series observations, while N is used to denote the number of cross-sectional units.

specific disturbance that is common to all cross sections. We find that the commonly used cure for this type of dependency, namely demeaning across the cross-sectional dimension, induces a size distortion when the cross-sectional dimension is small. This applies even if no time-specific disturbance is present. That is, the mere fact that a time-specific factor is allowed for affects the performance of the panel data stationarity test. To mitigate this size distortion, critical values, that can be used when cross-sectional correlation is modelled by a time-specific factor, are supplied. The new set of critical values work well regardless of whether a time-specific factor is present of not. Furthermore, the size distortions, that arises when a time-specific factor is allowed but not accounted for, are eliminated without any major sacrifices in the power of the panel data stationarity test.

The rest of this paper is organized as follows. In Section 2, the econometric model and the panel data stationarity test are introduced. Furthermore, in this section the effects of allowing for a time-specific disturbance is analyzed. Critical values that can be used when a time-specific disturbance is present are supplied in Section 3. The performance of the panel data stationarity test, using the supplied critical values, is studied in the same section. Finally, Section 4 offers some concluding remark.

2 Panel stationarity with a time-specific factor

2.1 The panel data model

The current paper is centered around the following panel-data unobserved components model:

$$y_{i,t} = \alpha_i + \delta_i t + \xi_{i,t} + \varepsilon_{i,t} \tag{1}$$
$$\xi_{i,t} = \xi_{i,t-1} + \nu_{i,t} \tag{2}$$
$$\varepsilon_{i,t} = \theta_t + \eta_{i,t} \tag{3}$$

The cross-section time-series, $y_{i,t}$, consists of three main components.[5] First, there are cross-section specific deterministic components, α_i and $\delta_i t$, which take the form of an intercept and a time trend. Second, $y_{i,t}$ includes of a random walk term, $\xi_{i,t}$. The development of this term is described in (2), where ν_{it} is $i.i.d.$ $N(0, \sigma^2_{,i})$. For all cases where $\sigma^2_{,i} > 0$, the cross-section time series $y_{i,t}$ will contain a unit root term, while it follows that $y_{i,t}$ is stationary, or trend stationary, if $\sigma^2_{,i} = 0$. In the latter case $\xi_{i,t}$ will reduce to $\xi_{0,i}$ for all t, which amount to a constant term that will be captured in the intercept when $y_{i,t}$ is detrended. Finally, $y_{i,t}$ includes a stochastic disturbance term, $\varepsilon_{i,t}$, which is described in (3). From (3) it can be seen that the composite disturbance term, $\varepsilon_{i,t}$, can be broken down into two components. The first of these is a time-specific disturbance, θ_t, which is assumed to be distributed $i.i.d.$ $N(0, \sigma^2)$. The second component, $\eta_{i,t}$, is assumed

[5]Here, and in the remainder of the paper, we let i denote the cross-sectional dimension and t denote the time-series dimension. Throughout we will also assume that $i \in \{1, \ldots, N\}$ and $t \in \{1, \ldots, T\}$.

to be an idiosyncratic disturbance that is distributed *i.i.d.* $N(0, \sigma^2)$. Hence, from (3) it can be seen that cross-sectional dependence between disturbances $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$, $i \neq j$, is introduced by the time-specific factor θ_t. It is the presence of θ_t that makes this model differ from the model in Hadri and Larsson (2005). If we let $\theta_t = 0$ for all $t \in \{1, \ldots, T\}$, the model in (1)-(3) would reduce to the model of Hadri and Larsson (2005), i.e. to the model with cross-sectionally independent disturbances, and hence it would be possible to apply the panel data stationarity test suggested by these authors. However, within the extended model where $\theta_t \neq 0$, the issue of cross-sectional correlation has to be addressed. In the following sections, we elaborate on the test of Hadri and Larsson (2005), discuss how it can be extended to allow for a time-specific factor and study how such an extension affects the small-sample behavior of the test.

2.2 The panel data stationarity test

The panel data stationarity tests of Hadri (2000) and Hadri and Larsson (2005) are developed within the unobserved components framework in (1)-(3) under the assumption that $\theta_t = 0$.[6] The panel data stationarity test, here denoted LM, is constructed by applying the stationarity test of Kwiatkowski et al. (1992) to each of the N time-series in the sample. By utilizing a standardized mean over the individual test statistics, a panel data stationarity test with a standard normal limiting distribution can be obtained. For the test of Hadri (2000), the asymptotic distribution is obtained by letting $T \to \infty$ followed by $N \to \infty$, while Hadri and Larsson (2005) obtains the limiting distribution by letting $N \to \infty$ for fixed T. In the current paper, we investigate the finite-sample behavior of the panel data stationarity test of Hadri and Larsson (2005) when time-specific disturbances are present, and hence stick to the fixed-T setting. The general expression for the panel data test statistic is given in (4), while the cross-section specific KPSS test statistics are calculated as in (5)-(7).

$$LM = \frac{\frac{1}{N}\sum_{i=1}^{N} LM_i - E(LM_i)}{\sqrt{\frac{Var(LM_i)}{N}}} \tag{4}$$

$$LM_i = \frac{T^{-2}\sum_{t=1}^{T} S_{i,t}^2}{\hat{\sigma}_{\varepsilon,i}^2} \tag{5}$$

$$S_{i,t} = \sum_{j=1}^{t} e_{i,j} \tag{6}$$

$$\widehat{\sigma}_{\varepsilon,i}^2 = T^{-1}\sum_{t=1}^{T} e_{i,t}^2 \tag{7}$$

[6] It is important to note that Hadri (2000) allows for the covariance stationary disturbance to be serially correlated, while Hadri and Larsson (2005) consider the case where the disturbance is serially independent.

In (6) and (7), $e_{i,t}$ denotes the OLS residual obtained after detrending $y_{i,t}$ with either an intercept or an intercept and a time trend. In (4), $E(LM_i)$ and $Var(LM_i)$ are the moments of the cross-section specific KPSS statistics. These moments depend, in the Hadri and Larsson (2005) setting, on the time-series dimension of the panel and on whether an intercept or an intercept and a time trend are used when detrending the series.

As noted above, the limiting distribution of the test statistic in (4) will not be standard normal as $N \to \infty$ if a time-specific factor, θ_t, is present. More specifically, the presence of cross-sectional correlation has been shown to cause size distortions in the panel data stationarity test (see e.g. Jönsson, 2004). Hence, it is desirable to account for the cross-sectional dependence in some way. Several methods for doing this are available. If a common factor structure is assumed, one could apply the panel data stationarity test Bai and Ng (2004a), which amounts to finding common factors by the method of principal components and then testing both the common factors and the de-factored series for stationarity. This method rests on asymptotics that require that both the cross-sectional and the time-series dimensions tend to infinity. Hence, it falls outside the framework of Hadri and Larsson (2005). Another test that allows for cross-sectional correlation is that of Harris et al. (2005). These authors propose a test based on autocovariances that has an asymptotic standard normal limit when $T \to \infty$ for fixed N. The same asymptotics applies for the test of Jönsson (2004), which is based on orthogonalization of $\varepsilon_{i,t}$ and hence of $y_{i,t}$. Evidently, these tests also fall outside the Hadri and Larsson (2005) framework. However, when the cross-sectional correlation in the panel data unit root and stationarity framework is caused by a time-specific factor, θ_t, Im et al. (1997), Shin and Snell (2006) and Jönsson (2006b) suggest that demeaning over the cross-sections provides a viable way of dealing with the size distortions that arise. Demeaning over cross sections amounts to constructing $\tilde{y}_{i,t} = y_{i,t} - N^{-1}\sum_{j=1}^{N} y_{j,t}$, and performing the test in (4)-(7) using the residuals obtained after detrending these series. In the next section, we go on by investigating how well the demeaning solution works in the context of the Hadri and Larsson (2005) panel data stationarity test.

2.3 Effects of a time-specific factor

When the cross-sectional dependence is modelled by a time-specific chock, i.e. when $\varepsilon_{i,t} = \theta_t + \eta_{it}$, where $\theta_t \sim i.i.d.\ N(0, \sigma^2)$ and $\eta_{i,t} \sim i.i.d.\ N(0, \sigma^2_{,i})$, demeaning over the cross-sectional dimension resolves the cross-sectional correlation problem.[7] The cross-sectionally corrected test is performed as above, with the only difference being that $\tilde{y}_{i,t} = y_{i,t} - \frac{1}{N}\sum_{j=1}^{N} y_{j,t}$ is used instead of $y_{i,t}$ when performing the test.

Recent results (see e.g. Jönsson, 2006b) have indicated that the demeaning procedure work unsatisfactory in small-N situations unless moments or critical values, especially obtained for the cross-sectionally corrected test, are used. More specifically, the demeaning procedure has been shown to introduce cross-sectional correlation, and hence a size distortion, in the panel data unit root framework even

[7] It should be noted, however, that other forms of cross-sectional dependency might not be addressed by demeaning the data (see e.g. Strauss and Yigit, 2003).

when disturbances are cross-sectionally independent. If this is the case also with the panel data stationarity test of Hadri and Larsson (2005), a new set of critical values is required for situations where the demeaning procedure is employed and the cross-sectional dimension is small.

In order to study the size of the Hadri and Larsson (2005) panel data stationarity test applied to demeaned series, data is generated according to the data generating process (DGP) in (8) below.

$$y_{i,t} = \alpha_i + \delta_i t + \epsilon_{i,t} \tag{8}$$

In (8), ϵ_{it} denotes a random disturbance term, which is assumed to be $i.i.d.$ $N(0, 1)$. Without loss of generality, we let $\alpha_i = 0$ and $\delta_i = 0$ in the DGP. Using the moments supplied by Hadri and Larsson (2005), the panel data test for the null hypothesis of stationarity is calculated as described above. In addition to calculating a test statistic for the case where the demeaning procedure is employed, we also obtain a panel data test statistic for the case where no cross-sectional correction is made. This is done in order to be able to single out the effects that are attributable to demeaning the data from the effects that are caused by making the normal approximation in a situation where N is fixed. These two tests are performed on 50,000 test statistics for panel dimensions where $T \in \{10, 20, 50, 100\}$, $N \in \{2, 3, \ldots, 10, 25, 50\}$ and various deterministic components are used in the detrending procedure. The resulting size of the tests, on the 10% significance level, is presented in Table 1.

As seen in Table 1, the panel data stationarity test is always over-sized whenever N is small, regardless of how large T is. For example, when T=10 and N=2 it can be seen that the size of the corrected test, i.e. the test applied to demeaned series, is 16.1% and 16.7% for the cases where an intercept and an intercept and a time trend are included in the detrending procedure. The same pattern can be seen for every parameter setup, and the conclusion that the test is upward size-distorted is undisputable. However, when we study the size results for the test based on series that have not been demeaned, it can be seen that a small upward size distortion exists also in this case, at least when N is small. Hence, the size distortion that was documented for the test employing a demeaning procedure obviously have two sources. The first source of the size distortion is the fact that we introduce some degree of cross-sectional correlation by demeaning the cross-section time series. The second source of the size distortion is the fact that N is small, maybe too small for the normal distribution to be accurately applied for inference. The relative importance of these two sources can be seen by comparing the size of the test that employs demeaning to the size of the test that does not.

As seen from Table 1, the size is somewhat higher than the significance level also for the uncorrected test, i.e. for the test denoted 'No corr.' in Table 1. Since the data is generated without a time-specific factor, the relative importance of the two sources for the size distortion can be easily identified. Comparing the size for the corrected and the uncorrected tests, it can be seen that the major part of the size distortion that occurs when $N < 10$, arises from the introduction of cross-sectional dependency through demeaning. However, the size distortion arising from inaccurate normal approximation is non-negligible. This fact suggests that the use of critical values for inference about the null hypothesis that all cross-section time series are stationary is preferable to the use of standardizing moments that take the demeaning procedure into account. While the use of especially obtained standardizing moments, as in Jönsson (2006b), will mitigate the effects of cross-sectional demeaning, the size distortions caused by inaccurate normal approximation will not be addressed. By using critical values, on the other hand, both sources for the size distortion can be mitigated.

In the next section, we supply response surface parameters that can be used to obtain critical values for the cross-sectionally corrected panel data stationarity test.

3 Small-sample distribution

As seen from the results in Table 1 and as concluded by Jönsson (2008), it can be suspected that the inappropriateness of normal approximation give rise to some size distortions in the Hadri and Larsson (2005) test, especially when N is small. This fact implies that it is desirable to work with critical values instead of relying on the normal approximation when conducting inference. Hence, we suggest holding on to the moments supplied by Hadri and Larsson (2005) when calculating the panel data stationarity test and, instead of critical values from the standard normal distribution, use finite-sample critical values obtained especially for the cross-sectionally corrected test. This approach will eliminate the size distortions arising from the poor normal approximation as well as the size distortions arising when introducing the demeaning procedure. Below, we will provide finite-sample critical values that can be used for inference about the stationarity hypothesis when a time-specific factor is modelled.

3.1 Critical values for the corrected test

In order to obtain critical values for the panel data test statistic, the cross-sectionally corrected panel data stationarity test statistic in (4) is calculated based on a set of artificially generated data series that are obtained as described in Section 2.3. In order to avoid vast tabulations with critical values, response surface regression can be fit and the parameters of the response surface regressions supplied. Hence, to be able to fit response surface regressions to the critical values, we obtain 50 critical values on the 10%, 5%, 2.5% and 1% significance levels based on 5,000 test statistics in each replication. The panel data dimensions considered are such that $T \in \{10, 20, \ldots, 100, 250, 500, 1000\}$, while $N \in \{2, 3, \ldots, 15, 20, 25, 50\}$. Critical values are obtained both for the case where an intercept is the only deterministic component and for the case where an intercept and a time trend are accounted for. This setup implies that each response surface regression is fitted to a sample consisting of 11,050 observations.

Based on the critical values obtained in the simulation we fit the response surface regression in (9) below.[8,9]

$$cv_{j,N,T} = \beta_0 + \sum_{i=1}^{2} \beta_{i,TS} T^{-i} + \sum_{i=1}^{2} \beta_{i,CS} N^{-i/2} + \beta_{CS,TS} N^{-0.5} T^{-2} + \epsilon_{j,N,T} \quad (9)$$

When estimated, the response surface parameters that are presented in Table 2 are obtained. The critical values calculated by using the response surface parameters of Table 2 can now be applied to obtain a panel data stationarity test that allows and accounts for cross-sectional correlation in the form of a time-specific disturbance. In order for the critical values based on the parameters in Table 2 to be useful, they should apply regardless of the degree of cross-sectional correlation that is present in the disturbances. Furthermore, in order for the the panel data stationarity test to work under heterogeneous alternatives, the cross-section demeaning procedure should be robust even if some of the cross sections are non-stationary, which means that the demeaning procedure should not annihilate the power of the test under such circumstances. To assure this, we set up and run a Monte Carlo simulation of the finite-sample size and power performance of the panel data stationarity test when a time-specific factor is allowed for and when the critical values that are supplied in the current paper are used for inference.

3.2 Finite-sample performance

In order to assess the performance of the demeaned panel data stationarity test when cross-sectional correlation is present, artificial data sets are once again generated and it is studied how well the panel data stationarity test performs when the critical values of the previous section are used.

In order to investigate how well the response surface parameters can reproduce accurate critical values, we run a Monte Carlo simulation where the data is demeaned prior to running the panel data stationarity test. In the simulations, 50,000 data sets are generated as in (8) for $N \in \{2, 3, 4, 5, 10, 25, 50\}$ and $T \in \{25, 50, 100, 250, 500\}$. To be able to assess the influence of cross-sectional dependence, as opposed to the mere influence of demeaning, we generate data both with and without cross-sectional dependence. That is, we consider the case where θ_t is added to the series and let $\theta_t = 0$ and $\theta_t \sim$ i.i.d. $N(0, 1)$, respectively. Furthermore, as it is desirable to consider the power of the panel data stationarity test, we also investigate the case where a number, N^{H_1}, of the cross sections contain a random walk component generated according to $\xi_{i,t} = \xi_{i,t-1} + \upsilon_{i,t}$, where $i \in \{1, \ldots, N^{H_1}\}$ and $\upsilon_{i,t} \sim i.i.d.\ N(0, 1)$.[10]

[8] The final specification in (9) was obtained after trying out various specifications for the response surface regressions. The final specification was chosen on the basis of in-sample fit.

[9] In (9), TS and CS refer to 'time series' and 'cross section', respectively.

[10] To reduce the influence of the initial condition, $_{i,0} = 0$, where $i \in \{1, \ldots, N^{H_1}\}$, for the random walk component, $T + 100$ time series observations are generated, while only the last T are used to construct the time series.

The size and power properties of the test, when no cross-sectional dependence is present, are given in Table 3 and Table 4, while the corresponding properties, when cross-sectional dependence is present, are seen in Table 5 and Table 6.[11] When comparing Table 3 and Table 5, it can be seen that the actual presence of cross-sectional correlation plays no role for the size properties of the test. Once a time-specific factor is accounted for, the test performs just as well when cross-sectional dependence is present as when it is not. The same results emerge for the power properties of the panel data stationarity test. As seen in Table 4 and Table 6, the power of the test is unaffected by the actual presence of cross-sectional correlation, as long as we allow for it by accounting for a time-specific disturbance term. Moreover, it can be seen from Table 4 and Table 6 that, in both cases, the test fares well when a subset of the cross sections display a unit root behavior.

4 Conclusions

In this paper, we show that the panel data stationarity test of Hadri and Larsson (2005) has a size distortion when the cross-sectional dimension is small and a time-specific factor is accounted for by demeaning over cross sections. We supply response surface parameters that can be used to calculate critical values that take this correction for cross-sectional correlation into account. The supplied critical values make the size distortions disappear and it is also proved that the test maintains good power properties even after allowing for cross-sectional correlation through a time-specific factor.

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References

Bai, J. and Ng, S. (2004a). A New Look at Panel Testing of Stationarity and the PPP Hypothesis. In Andrews, D. and Stock, J. H., editors, *Identication and Inference in Econometric Models: Essays in Honor of Thomas J. Rothenberg.* Cambridge University Press.

Bai, J. and Ng, S. (2004b). A PANIC Attack on Unit Roots and Cointegration. *Econometrica*, 72(4):1127–1177.

[11] We have also investigated other time-series dimensions than the ones presented in the tables. The main conclusions that follow from the tables remain unchanged also when the time-series dimensions are chosen outside the set used for fitting the response surface regressions.

Breitung, J. and Pesaran, M. H. (2008). Unit Roots and Cointegration in Panels. In Mátyás, L. and Sevestre, P., editors, *The Econometrics of Panel Data, Third Edition*.

Carrion-I-Silvestre, J. L., Del Barrio, T., and López-Bazo, E. (2004). Evidence on the Purchasing Power Parity in a Panel of Cities. *Applied Economics*, 36:961–966.

Chang, Y. (2002). Nonlinear IV Unit Root Tests in Panels with Cross-Sectional Dependency. *Journal of Econometrics*, 110:261–292.

Chang, Y. (2004). Bootstrap Unit Root Tests in Panels with Cross-Sectional Dependency. *Journal of Econometrics*, 120:263–293.

Choi, I. (2006). Nonstationary Panels. In Mills, T. C. and Patterson, K., editors, *Palgrave Handbook Of Econometrics Econometric Theory. Volume 1: Econometric Theory*. Palgrave MacMillan, USA.

Groen, J. and Kleibergen, F. (2003). Likelihood-Based Cointegration Analysis in Panels of Vector Error-Correction Models. *Journal of Business and Economic Statistics*, 21(2):295–318.

Hadri, K. (2000). Testing for Stationarity in Heterogeneous Panel Data. *Econometrics Journal*, 3:148–161.

Hadri, K. and Larsson, R. (2005). Testing for Stationarity in Heterogeneous Panel Data where the Time Dimension is Finite. *Econometrics Journal*, 8:55–69.

Harris, D., Leybourne, S., and McCabe, B. (2005). Panel Stationarity Tests for Purchasing Power Parity with Cross-Sectional Dependence. *Journal of Business and Economic Statistics*, 23(4):395–409.

Holmes, M. J. (2002). Panel Data Evidence on Inflation Convergence in the European Union. *Applied Economics Letters*, 9:155–158.

Im, K., Pesaran, M., and Shin, Y. (1997). Testing for Unit Roots in Heterogeneous Panels. Mimeographed.

Im, K., Pesaran, M., and Shin, Y. (2003). Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics*, 115:53–74.

Jönsson, K. (2004). Testing for Stationarity in Panel Data Models when Disturbances are Cross-Sectionally Correlated. Working Paper 2004:17, Department of Economics, Lund University.

Jönsson, K. (2005). Cross-Sectional Dependency and Size Distortion in a Small-Sample Homogeneous Panel Data Unit Root Test. *Oxford Bulletin of Economics and Statistics*, 67(3):369–392.

Jönsson, K. (2006a). Testing for Stationarity in Panel Data when Errors are Serially Correlated: Finite-Sample Results. Working Paper 2005:16, Department of Economics, Lund University. Revised December 2006.

Jönsson, K. (2006b). Time-Specific Disturbances and Cross-Sectional Dependency in a Small-Sample Heterogeneous Panel Data Unit Root Test. *Applied Economics*, 38:1309–1317.

Jönsson, K. (2008). The Accuracy of Normal Approximation in a Heterogeneous Panel Data Unit Root Test. *Statistical Papers*, 49(3):565–579.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., and Shin, Y. (1992). Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root. *Journal of Econometrics*, 54:159–178.

Larsson, R., Lyhagen, J., and Löthgren, M. (2001). Likelihood-based Cointegration Tests in Heterogenous Panels. *Econometrics Journal*, 4:109–142.

Lee, H.-Y. and Wu, J.-L. (2004). Convergence of Interest Rates Around the Pacific Rim. *Applied Economics*, 36:1281–1288.

Levin, A. and Lin, C.-F. (1992). Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties. Discussion paper #92-93, University of California, San Diego.

Levin, A. and Lin, C.-F. (1993). Unit Root Tests in Panel Data: New Results. Discussion paper #93-56, University of California, San Diego.

Levin, A., Lin, C.-F., and Chu, C.-S. J. (2002). Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties. *Journal of Econometrics*, 108:1–24.

McCoskey, S. and Kao, C. (1998). A Residual Based Test of the Null of No Cointegration in Panel Data. *Econometric Reviews*, 17(1):5784.

Moon, H. R. and Perron, B. (2004). Testing for a Unit Root in Panels with Dynamic Factors. *Journal of Econometrics*, 122:81–126.

O'Connell, P. G. J. (1998). The Overvaluation of Purchasing Power Parity. *Journal of International Economics*, 44:1–19.

Pedroni, P. (1999). Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. *Oxford Bulletin of Eocnomics and Statistics*, 61:653–670. Special issue.

Pedroni, P. (2004). Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. *Econometric Theory*, 20:597–625.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2):265–312.

Phillips, P. C. B. and Sul, D. (2003). Dynamic Panel Estimation and Homogeneity Testing under Cross Section Dependence. *Econometrics Journal*, 6:217–259.

Quah, D. (1994). Exploiting Cross-Section Variation for Unit Roots Inference in Dynamic Data. *Economics Letters*, 44:9–19.

Shin, Y. and Snell, A. (2006). Mean Group Tests for Stationarity in Heterogeneous Panels. *Econometrics Journal*, 9:123–158.

Strauss, J. and Yigit, T. (2003). Shortfalls of Panel Unit Root Testing. *Economics Letters*, 81:309–313.

Westerlund, J. (2005). A Panel CUSUM Test of the Null of Cointegration. *Oxford Bulletin of Economics and Statistics*, 67(2):231–262.

Table 1: Size of panel data stationarity tests.[a,b]

		Intercept		Trend				Intercept		Trend	
T	N	No corr.	Corr.	No corr.	Corr.	T	N	No corr.	Corr.	No corr.	Corr.
10	2	0.116	0.161	0.114	0.167	20	2	0.111	0.144	0.108	0.157
	3	0.116	0.148	0.111	0.150		3	0.109	0.138	0.108	0.142
	4	0.113	0.136	0.110	0.137		4	0.111	0.133	0.109	0.136
	5	0.110	0.129	0.112	0.128		5	0.111	0.132	0.108	0.129
	6	0.110	0.125	0.111	0.125		6	0.113	0.127	0.108	0.125
	7	0.108	0.121	0.106	0.121		7	0.109	0.120	0.107	0.121
	8	0.107	0.116	0.107	0.119		8	0.109	0.118	0.108	0.119
	9	0.109	0.118	0.111	0.119		9	0.107	0.119	0.107	0.118
	10	0.109	0.117	0.106	0.116		10	0.109	0.119	0.107	0.116
	25	0.105	0.107	0.104	0.107		25	0.105	0.109	0.106	0.110
	50	0.103	0.104	0.103	0.105		50	0.106	0.109	0.105	0.107
		Intercept		Trend				Intercept		Trend	
T	N	No corr.	Corr.	No corr.	Corr.	T	N	No corr.	Corr.	No corr.	Corr.
50	2	0.106	0.137	0.104	0.149	100	2	0.104	0.136	0.106	0.148
	3	0.107	0.135	0.106	0.135		3	0.106	0.133	0.105	0.135
	4	0.107	0.129	0.105	0.129		4	0.107	0.127	0.107	0.133
	5	0.108	0.127	0.108	0.128		5	0.108	0.126	0.107	0.125
	6	0.108	0.125	0.106	0.122		6	0.106	0.122	0.107	0.121
	7	0.108	0.120	0.109	0.124		7	0.107	0.120	0.105	0.119
	8	0.107	0.120	0.105	0.117		8	0.106	0.117	0.106	0.118
	9	0.108	0.118	0.106	0.116		9	0.108	0.118	0.105	0.118
	10	0.107	0.116	0.106	0.114		10	0.108	0.116	0.106	0.116
	25	0.105	0.109	0.107	0.111		25	0.108	0.112	0.105	0.110
	50	0.102	0.104	0.105	0.107		50	0.105	0.107	0.106	0.107

Notes: [a]'No corr.' refers to the case where no correction is made in order to account for cross-sectional correlation. 'Corr.' refers to the case where the cross-sectional mean is subtracted from each time-series observation.
[b] Data is generated as $y_{i,t} = \epsilon_{i,t}$, with $\epsilon_{i,t} \sim N(0,1)$.

Table 2: Response surface parameters for critical values.

Intercept							
Sig. Level	β_0	$\beta_{1,TS}$	$\beta_{2,TS}$	$\beta_{1,CS}$	$\beta_{2,CS}$	$\beta_{CS,TS}$	R^2
10%	1.317	0.387	-15.564	-0.023	0.900	38.309	0.889
5%	1.793	-0.304	-9.666	-0.383	2.596	19.337	0.957
2.5%	2.241	-1.501	7.247	-0.828	4.530	-24.375	0.967
1%	2.784	-3.711	41.326	-1.386	7.174	-107.421	0.967
Intercept and trend							
Sig. Level	β_0	$\beta_{1,TS}$	$\beta_{2,TS}$	$\beta_{1,CS}$	$\beta_{2,CS}$	$\beta_{CS,TS}$	R^2
10%	1.347	0.233	-11.488	-0.278	1.302	26.713	0.914
5%	1.805	-0.490	-4.170	-0.593	2.757	6.036	0.958
2.5%	2.223	-1.416	9.018	-0.945	4.361	-32.051	0.966
1%	2.739	-3.181	39.163	-1.454	6.639	-111.125	0.965

Table 3: Size of demeaned test.[a]

Intercept					
N	T=25	T=50	T=100	T=250	T=500
2	0.052	0.053	0.050	0.050	0.052
3	0.049	0.049	0.050	0.049	0.050
4	0.048	0.047	0.050	0.048	0.049
5	0.049	0.049	0.050	0.049	0.049
10	0.052	0.050	0.050	0.050	0.052
25	0.050	0.049	0.049	0.049	0.050
50	0.047	0.049	0.048	0.048	0.049
Intercept and trend					
N	T=25	T=50	T=100	T=250	T=500
2	0.052	0.052	0.050	0.049	0.048
3	0.048	0.048	0.048	0.048	0.048
4	0.047	0.048	0.050	0.048	0.050
5	0.048	0.050	0.050	0.050	0.050
10	0.050	0.051	0.050	0.052	0.051
25	0.050	0.050	0.050	0.047	0.049
50	0.048	0.046	0.046	0.048	0.048

Notes: [a] Data is generated as $y_{i,t} = \epsilon_{i,t}$, with $\epsilon_{i,t} \sim N(0,1)$.

Table 4: Power of demeaned test.[a,b]

Intercept						
N	N^{H_1}	T=25	T=50	T=100	T=250	T=500
2	1	0.693	0.896	0.982	0.999	1.000
3	1	0.705	0.903	0.984	1.000	1.000
4	2	0.905	0.990	1.000	1.000	1.000
5	2	0.900	0.990	1.000	1.000	1.000
10	5	0.997	1.000	1.000	1.000	1.000
25	12	1.000	1.000	1.000	1.000	1.000
50	25	1.000	1.000	1.000	1.000	1.000

Intercept and trend						
N	N^{H_1}	T=25	T=50	T=100	T=250	T=500
2	1	0.510	0.850	0.983	1.000	1.000
3	1	0.518	0.854	0.986	1.000	1.000
4	2	0.758	0.982	1.000	1.000	1.000
5	2	0.737	0.978	1.000	1.000	1.000
10	5	0.969	1.000	1.000	1.000	1.000
25	12	1.000	1.000	1.000	1.000	1.000
50	25	1.000	1.000	1.000	1.000	1.000

Notes: [a]We use N^{H_1} to denote the number of cross sections that are non-stationary under the alternative hypothesis.
[b]Data is generated as $y_{i,t} = \epsilon_{i,t} + \xi_{i,t}$, with $\epsilon_{i,t} \sim N(0,1)$ and $\xi_{i,t} = 0$ for $N - N^{H_1}$ cross-sectional units and $\xi_{i,t} = \xi_{i,t-1} + \upsilon_{i,t}$, with $\upsilon_{i,t} \sim N(0,1)$, for N^{H_1} cross-sectional units.

Table 5: Size of demeaned test when CSD is present.[a]

Intercept					
N	T=25	T=50	T=100	T=250	T=500
2	0.052	0.052	0.051	0.051	0.050
3	0.047	0.049	0.049	0.048	0.047
4	0.049	0.050	0.049	0.050	0.051
5	0.050	0.049	0.052	0.049	0.050
10	0.050	0.050	0.049	0.052	0.049
25	0.050	0.048	0.050	0.050	0.049
50	0.048	0.046	0.049	0.049	0.047

Intercept and trend					
N	T=25	T=50	T=100	T=250	T=500
2	0.052	0.051	0.049	0.050	0.048
3	0.049	0.048	0.046	0.049	0.050
4	0.048	0.051	0.048	0.048	0.049
5	0.048	0.049	0.049	0.049	0.050
10	0.050	0.050	0.050	0.050	0.051
25	0.049	0.050	0.049	0.051	0.050
50	0.046	0.047	0.046	0.049	0.047

Notes: [a] Data is generated as $y_{i,t} = \epsilon_{i,t} + \theta_t$, with $\epsilon_{i,t} \sim N(0,1)$ and $\theta_t \sim N(0,1)$.

Table 6: Power of demeaned test when CSD is present.[a,b]

Intercept						
N	N^{H_1}	T=25	T=50	T=100	T=250	T=500
2	1	0.689	0.896	0.982	1.000	1.000
3	1	0.704	0.904	0.985	1.000	1.000
4	2	0.905	0.991	1.000	1.000	1.000
5	2	0.901	0.990	1.000	1.000	1.000
10	5	0.997	1.000	1.000	1.000	1.000
25	12	1.000	1.000	1.000	1.000	1.000
50	25	1.000	1.000	1.000	1.000	1.000
Intercept and trend						
N	N^{H_1}	T=25	T=50	T=100	T=250	T=500
2	1	0.508	0.852	0.985	1.000	1.000
3	1	0.513	0.858	0.985	1.000	1.000
4	2	0.756	0.981	1.000	1.000	1.000
5	2	0.737	0.980	1.000	1.000	1.000
10	5	0.969	1.000	1.000	1.000	1.000
25	12	1.000	1.000	1.000	1.000	1.000
50	25	1.000	1.000	1.000	1.000	1.000

Notes: [a]We use N^{H_1} to denote the number of cross sections that are non-stationary under the alternative hypothesis.
[b]Data is generated as $y_{i,t} = \epsilon_{i,t} + \theta_t + \xi_{i,t}$, with $\epsilon_{i,t} \sim N(0,1)$, $\theta_t \sim N(0,1)$ and $\xi_{i,t} = 0$ for $N - N^{H_1}$ cross-sectional units and $\xi_{i,t} = \xi_{i,t-1} + \upsilon_{i,t}$, with $\upsilon_{i,t} \sim N(0,1)$, for N^{H_1} cross-sectional units.